Hospital beds and waiting lists: A simulation analysis*

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Abstract

Waiting time for elective surgery is a significant problem in the current medical world. This paper aims to reproduce, by means of a simulation model, how the endowment of hospital's capital (roughly measured by the number of beds) affects the length of stay (inpatient activity) and, consequently, the waiting list. We simulate inpatient activity by fitting a Normal distribution to real impatient activity data observed in 2007, and model the effect of number of beds on inpatient activity by using a linear regression model. The analysis is performed by first assuming that the number of beds does not affect the inpatient activity or the length of stay (absence of beds effect), and then assuming that the number of beds has a linear impact on inpatient activity by adapting itself to the new conditions. The research allows us to evaluate the drop in waiting lists due to a potential increase of beds.

Keywords: Hospital beds, inpatient activity, Monte Carlo simulation, waiting lists

JEL Classification:

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1. Introduction

A waiting list for healthcare is a queue of patients who have been given a care procedure but for reasons beyond their control must wait to be served a variable period of time (Sampietro and Espallargues, 2001). Waiting lists appear in different care fields (primary and specialty care) and in different levels of care (outpatient and hospital care), and in different therapeutic procedures (surgical and nonsurgical), diagnostic and rehabilitative (Churruca, 2000). However, it is customary to discuss waiting lists referring to the surgical waiting lists. These have been studied more frequently, citing major problems of morbidity and mortality, as well as greater economic impact (Instituto Nacional de la Salud, 1998). With the aim of assessing the influence of waiting lists on survival rates, Richards (1999) reviewed 87 studies published in different countries and found that survival of patients with more than three months of delay on surgical treatment of breast cancer was reduced by 10% at 5 years as compared with those patients who benefit from earlier operations. In the same line, Silber et al. (1996) examined the risk associated with waiting lists and found that the risk of mortality in patients awaiting coronary by-pass was 1.3% per month and that to minimize the risk of death on the waiting list, the by-pass should be performed within the first week after the diagnosis of coronary angiography.

In Spain, there is a waiting list for programmed surgery to such an extent that a public opinion barometer has identified waiting time for elective surgery as the leading source of public dissatisfaction with inpatient services. One of the main reasons explaining waiting lists for elective surgery is the fact that Spanish hospitals have serious problems concerning productive capacity. Although productive capacity refers to resources as staff, beds, operating theatres and community-based health centers to name a few, the two main in a hospital production function are the personnel and the number of beds (often considered a rough proxy for capital endowment).

In this paper, we analyze the situation in one of these hospitals. Specifically, we study how the number of beds—a scarce and expensive input in healthcare—affects the daily inpatient activity, the patients' length of stay and, consequently, the hospital waiting list. However, a number of technical and financial problems make it impossible to experiment with the real hospital configuration to examine the effect of the number of beds on inpatient activity and waiting lists. In our case, experimentation with the real system would cause a lot of trouble both for patients and staff. For that reason, we are obliged to perform a simulation approach, which represents the real system and can be manipulated without disrupting the real healthcare practice. Indeed, one of the often-mentioned reasons for using simulation as a tool is the experimentation with non-existing systems (Law and Kelton, 1991). Once validated, the simulated model can yield accurate estimates of the behavior of the real system and help in understanding and clarifying complicated dynamic processes (Yamaguchi et al., 1994).

Simulation also offers an easily way to investigate the effect of different alternatives in situation where actual experiments are impossible, too costly, time consuming or risky (Lagergren, 1998). By this approach we are able to learn how the system responds to different changes in assumptions and to reveal decisive factors (Lubicz and Mielczarek, 1987). Finally, simulate a process, like admission to elective surgery, could also help in identifying bottle-neck and congestion points. In addition, the simulation model can be useful for monitoring the performance of the hospital system and as a planning tool to assess the relative effectiveness of alternative policies in coping with historical or statistically generated patient load.

In sum, simulation is a recommended tool to solve those problems of complex systems, where the use of mathematical models is not operational. For that, it is widely used to analyze hospital problems because such problems are considered a complex system, with many variables and different random events. For example, in surgical services, Everett (2002) developed a decision support tool to evaluate various policies on wait lists and bed occupancy. Akkerman and Knip (2004) used simulation to allocate beds to cardiac surgery in order reduce waiting times. Denton et al. (2007) applied simulation to examine optimal timing of surgery. VanBerkel and Blake (2007) developed a discrete event simulation model to evaluate surgical wait times and support capacity planning decisions. Although the optimization approach is different in each case, the goal is to improve all services through the optimal use of resources.

To examine the pattern of waiting lists in programmed surgery, at aiming to reproduce the behavior of the daily inpatient activity, the length of stay and, consequently, the waiting list, we fit a known distribution to each variable, which allows us to generate new values for the daily inpatient activity and the patients' length of stay by means of a Monte-Carlo method. Once new observations of the inpatient activity and the stays length are generated, we can also create the corresponding simulated waiting list and the daily percentage of occupied beds (the occupancy rate).

We also examine how the waiting lists vary when hospital beds (rough proxy for capital input) increase. This is done by examining how the number of beds affects the inpatient activity, the stays length and, consequently, the waiting list. For achieving this objective, we replicate the simulation process for various increased percentages in the number of beds available in two alternative scenarios. First, we assume that an increase in the number of beds does not modify the pattern of the inpatient activity; then, we assume that a change in the number of beds modifies the behavior of the inpatient activity in the amount given by the inpatient activity-beds elasticity. All the computational programming was performed using the statistical free software R.

Our research provides two main results. If there are no beds effects, any increase in the number of beds leads waiting lists to disappear and the daily occupancy rate to drastically reduce, even when beds increase is small. By contrast, if the elasticity of the beds-inpatient activity relationship is taking into account, there are no significant differences in terms of occupancy rates and waiting lists as the number of beds in the hospital increases. In other words, if the elasticity is included in the simulation model, waiting lists do not drop when the teaching hospital has more capital in its production function.

Our results are closed to those obtained by Kroneman and Siegers (2004). In examining the effect of hospital beds on the use of them for 10 European countries, these authors find that admission rates appear to be sensitive to bed supply, and exhibits a positive elasticity of 1.44. Hospitals of those countries with a high number of beds show higher admission rates, but the number of beds does not seem to have a significant impact on the average length of stays. Zeraati et al. (2005) suggest that an increase in the number of hospital beds tends to generate additional demand, either in the form of more patients admitted, patients treated for longer periods or some combination of the two. This fact reflects the so-called Roemer's Law (Roemer, 1961) indicating that a sudden increase in the hospitals beds in a given country, with no changes in other factors, leads to a sharp increase in usage rates.

The remainder of the paper is organized as follows. In Section 2, we first present the model. Then, in Section 3, we provide the simulation analysis and the main results. Finally, in Section 4 we discuss the results achieved.

2. The model

2.1. Data on inpatient activity and the length of stay

The approach was applied at the Complejo Hospitalario Universitario de Santiago (CHUS) in Santiago de Compostela, Spain. CHUS is the largest teaching hospital for Galician's ... residents and as well serves as a regional hospital for approximately ... residents in Galicia. In 2007, CHUS ran

1,110 inpatients beds, of which about... are "reserved" for surgical patients. [1]

Our working variables are the daily inpatient activity and the length of stay for all patients admitted to the hospital in 2007. To fit a pattern of the inpatient activity from real data and select an adequate fitting distribution, we split data into two groups: working days (Monday to Friday, except July, August and December days) and holidays (Saturdays and Sundays plus July, August and December days). This is done because, as plotted in Figure 1, we observed clear differences between values of the inpatient activity for working days and inpatient activity for holidays.

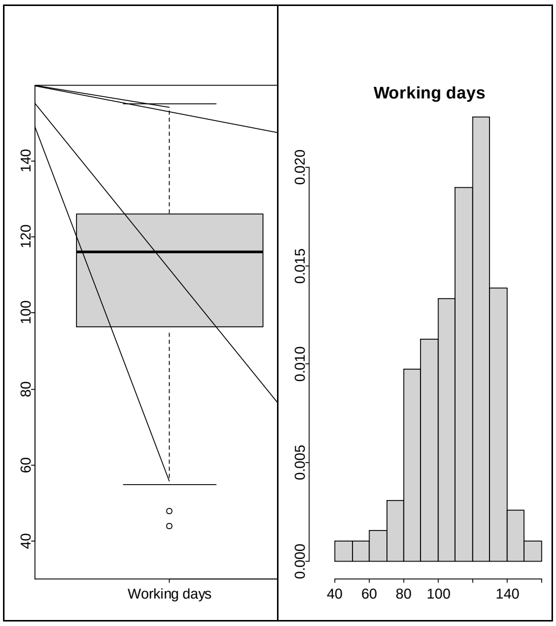


Figure 1. Box-plot (left panel) and histogram (right panel) of daily inpatient activity.

In fact, quartiles are 96.5 (first quartile), 116 (median) and 126 days (third quartile) for the working days, and 53 (first quartile), 80.5 (median) and 94 days (third quartile) for holidays. Besides, a two-sample Kolmogorov-Smirnov test applied to data shows that the statistic value is 0.5667 and the associated p-value is smaller than 0.05, so the null hypothesis that inpatient activity in working days and in holidays is drawn from the same distribution of probability can be rejected. Hence, we decided to analyze separately the inpatient activity in working days and in holidays.

The box-plot and the histogram of the patients' length of stay are plotted in Figure 2, where it can be seen that most of data are short stays since the first quartile is 3 days, the median is 6 days, and the third quartile is 12 days, although there are outliers that correspond to the longer stays in hospital.

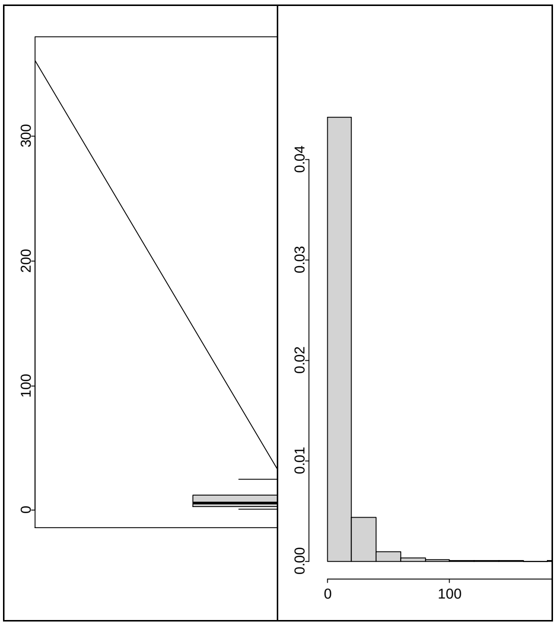


Figure 2. Box-plot (left panel) and histogram (right panel) of length of stay.

[1] Consellería de Sanidade, Xunta de Galicia (2008), Memoria 2007 Sistema Público de Saúde de Galicia. Available at <http://www.sergas.es/Publicaciones/DetallePublicacion.aspx?IdPaxina=40008&IDCatalogo=1732>.

2.2. The Monte Carlo simulation method

The Monte Carlo approach allows us to generate new values for the daily inpatient activity and the patients' length of stay. For the inpatient activity, we have considered the data as independent observations of a continuous variable, and then fitted a Normal distribution for working days and holidays separately.[2] In other words, we have estimated the two parameters (the mean μ and the standard deviation σ) that determine a Normal distribution for working days and holidays. After the fitting procedure, we selected the Normal distribution

$$N(\hat{\mu}_W = 112.02, \hat{\sigma}_W = 20.45), \quad (1)$$

for the inpatient activity in a working day (denoted by subscript *W*) and the Normal distribution

$$N(\hat{\mu}_H = 76.72, \hat{\sigma}_H = 24.08), \quad (2)$$

for the inpatient activity in a holiday (denoted by subscript *H*). To check if the Normal distribution captures correctly the behavior of the inpatient activity variable, we also performed a Kolmogorov-Smirnov test, which offered 0.0972 as the value of the statistics for the working days (p-value equals to 0.0503), and 0.1047 for the holidays (p-value equals to 0.0481). Then we accepted the normality for $\alpha = 0.01$.

Regarding the length of the stay in the hospital, we have fitted a Normal and other known distributions like a Poisson distribution, but none of them gave us a good fitting. A possible cause could be the presence of outliers corresponding to large stays, which leads the considered distributions do not have tails heavy enough to fit adequately the real data. Hence, we choose an alternative approach based on the kernel density estimator for which we implicitly assume the variable (the stays length) is continuous. Denoting the real observations of stays length in 2007 by X_1, X_2,..., X_n, where *n* represents the size of the sample, the density function *f* of the stays length variable can be estimated by the kernel estimator (Wand and Jones, 1995)

$$\hat{f}_h(x) = \frac{1}{n \times h} \sum_{i=1}^{n} K\left(\frac{x - X_i}{h} \right), \quad (3)$$

where *K* is a kernel function satisfying the property $\int K(x)dx = 1$ (usually, *K* is a unimodal symmetric probability density function) and *h* is a positive number called bandwidth related with the smoothness of the obtained estimator. Specifically, we have adopted as the kernel function the standard normal density function and we have estimated the bandwidth related with

[2] Although we have tried to fit distributions other than Normal distribution, the best fitting was reached using the latter.

the smoothness of the obtained estimator $\hat{h} = 0.74$.

2.3. Generating new observations

Once the distributions for daily inpatient activity and patients' length of stay have been chosen, we generate data for both variables. A new observation for inpatient activity is drawn from the Normal distribution stated in (1) if the corresponding day is a working day, and from the Normal distribution postulated in (2) for a holiday. In turn, the new observations for patients' length of stay have been obtained from the kernel estimator stated in (3). This is done by means of a three-stage method as follows. In the first stage, we denote as x_1, x_2,..., x_n the real length of stay in 2007 and we randomly select one element x of the dataset $\{x_1, x_2, \ldots, x_n\}$. In the second stage, we generate z from a standard Normal distribution $z \to N(0,1)$. Finally, in the third stage, a new length of stay, x^*, is built by using the rule

$$x^* = round(x + \hat{h} z), \quad (4)$$

where $\hat{h}$ is the estimated bandwidth for the kernel density estimator (3) and $round(\cdot)$ rounds the simulated values x^* to zero decimal places.

3. Simulating the inpatient activity and the patients' length of stay

We can now simulate the hospital activity for 2007 when the total number of beds was 1,100. To avoid starting with an "empty" system (a hospital without patients), the simulation process begins on August 1st 2006, i.e. before the period of analysis.[3] Then for each day of 2007, the simulation process followed a three-stage procedure. In the first stage, we generate an inpatient activity value, taking into account both new patients and waiting-list patients. In the second stage, we detect the number of free beds in the hospital and we decide to occupy them with patients for which generate the length of their stays. In the third stage, if the daily inpatient activity exceeds the number of beds available, the remaining patients are put on the waiting list.

The results of this three-step model are depicted in Figures 3 and 4. Figure 3 plots the actual inpatient activity of the hospital in 2007 (black line) and the 500 runs of inpatient activity simulated by means of this three-step model (grey lines). On the other hand, Figure 4 depicts the 500 replications of simulated daily waiting lists.

[3] In the simulation literature, this is called the start-up problem (Law, 1983).

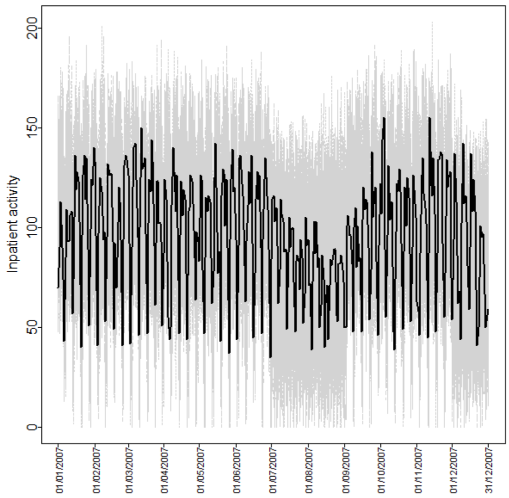


Figure 3. Actual inpatient activity (solid black line) and simulated inpatient activity (grey lines) in 2007.

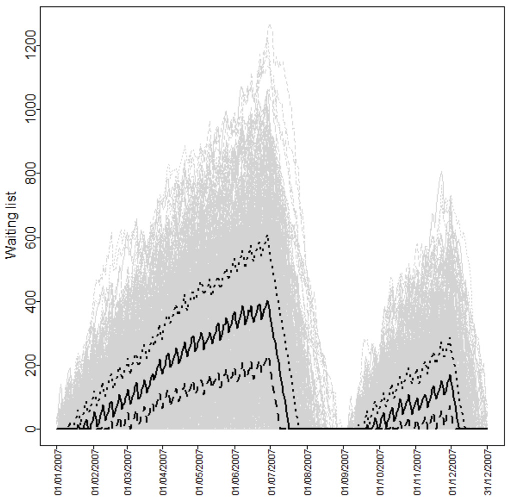


Figure 4. Simulated daily waiting list (grey lines) in 2007. Waiting list quartiles are highlighted: 25% (dashed black line), 50% (solid black line) and 75% (dotted black line).

We can conclude that the simulated values fit well the pattern of the real data for this period. Besides, the waiting list in the hospital increases until June, disappears during July and August, and picks up again until December. There are then two critical moments located before summer and Christmas with very high peaks. A similar pattern is observed in the daily occupancy rate plotted in Figure 5.

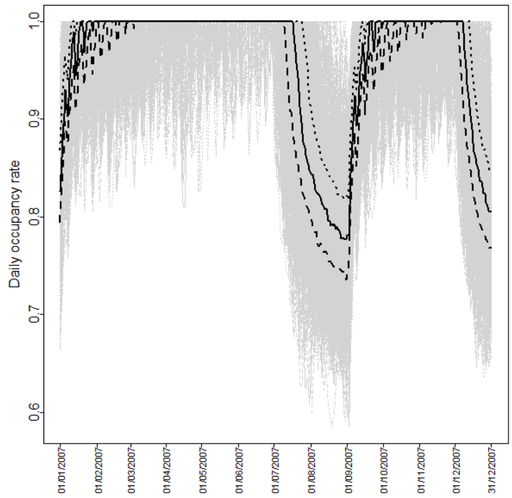


Figure 5. Simulated daily occupancy rate (grey lines) in 2007. Occupancy rate quartiles are highlighted: 25% (dashed black line), 50% (solid black line), and 75% (dotted black line).

Finally, Figure 6 and 7 summarize the results obtained for the daily waiting list and the occupancy rate. For example, we can see that there is no waiting list for 38% of days, but the hospital is fully occupied for 62% of days. Indeed, 14% of days are characterized by the existence of more than 350 patients within the waiting list.

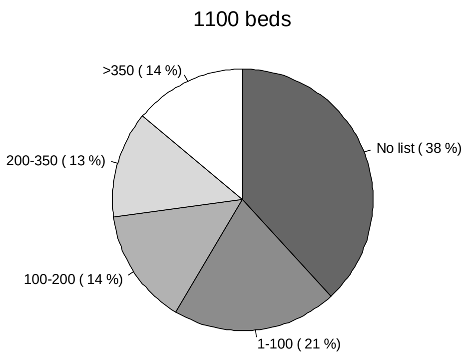


Figure 6. Pie chart for simulated daily waiting list data

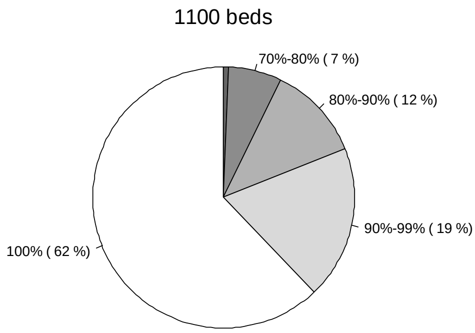


Figure 7. Pie chart for simulated daily occupancy rate.

3.1. The beds-inpatient activity elasticity

In this subsection we examine what happens in the simulation analysis if the number of hospital beds (roughly speaking, the amount of physical capital) increases. To this end, we assume two alternative scenarios. First, in Scenario 1 the number of beds has no impact on the inpatient activity and on stays pattern. Then, this assumption is removed in Scenario 2. In both cases, we assume the actual number of beds (1,100), as well as successive increments of beds: 1,155 (an increase of 5% with respect to the actual number of beds), 1,210 (an increase of 10%), 1,265 (an increase of 15%), 1,320 (an increase of 20%), 1,430 (an increase of 30%), 1,540 (an increase of 40%) and 1,650 (an increase of 50%).

3.1.1. Scenario 1

Here the daily inpatient activity is simulated as described above-mentioned; that is, $\hat{\mu}_W$ and $\hat{\sigma}_W$ ($\hat{\mu}_H$ and $\hat{\sigma}_H$) are estimated using the inpatient activity sample of working days (holidays).

This implies that none increase on the number of beds in the hospital modifies the generation process of new values for the inpatient activity or the stays length. In this context, Figure 8 and 9 show, respectively, the median of the 500 simulated waiting lists and the median of the 500 simulated occupancy rates both for the various amounts of beds.

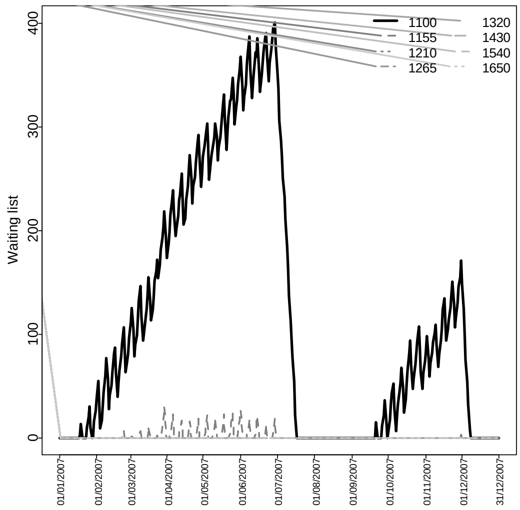


Figure 8. Median of simulated waiting lists.

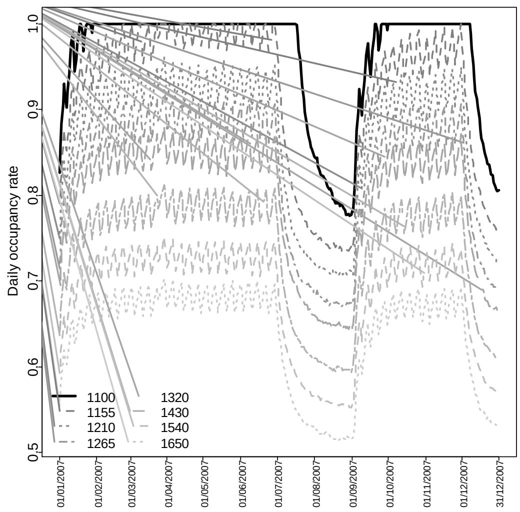


Figure 9. Median of simulated daily occupancy rate.

The obtained under Scenario 1 can be formally recorded as follows.

Proposition 1. *If the number of beds has no impact on inpatient activity, even a minor increase in the number of beds leads (i) the waiting list to disappear, and (ii) the occupancy rate to drastically reduce.*

Part (i) of Proposition 1 is illustrated in Figure 10.

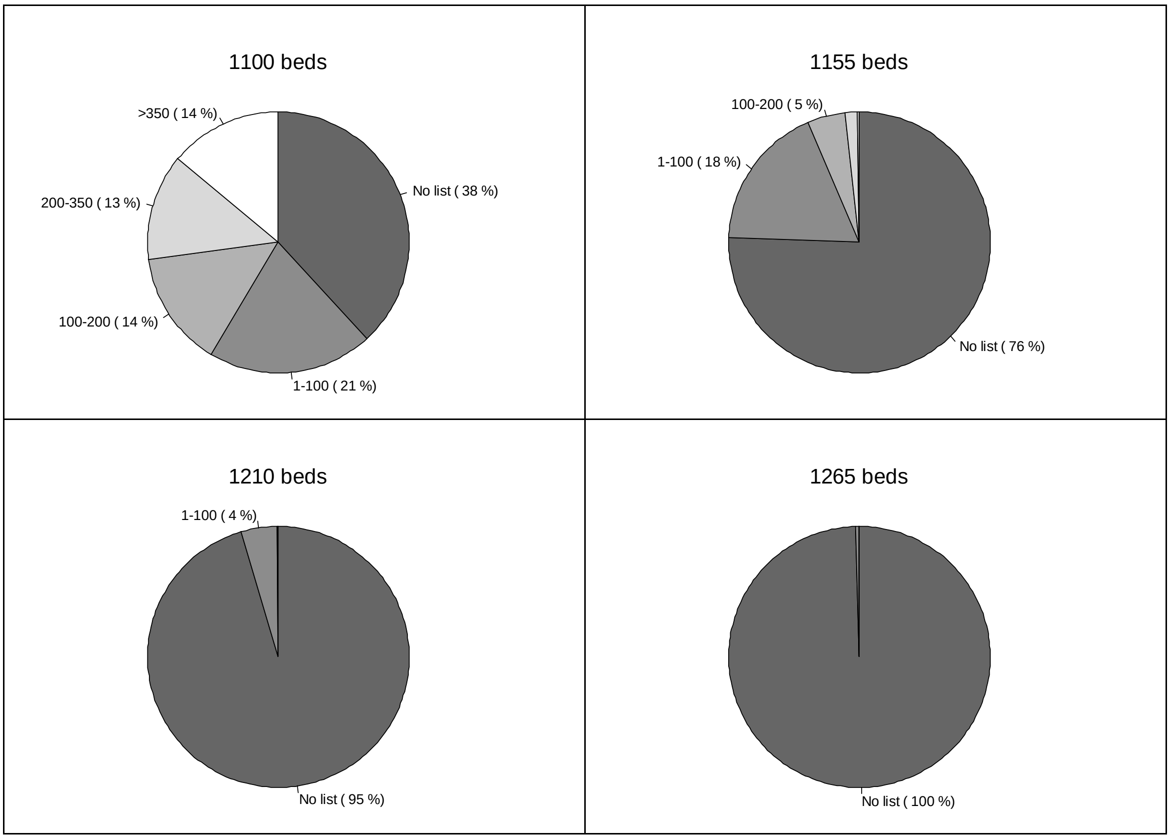


Figure 10. Pie charts for simulated daily waiting list data.

It can be observed that a sufficiently small increase of beds leads the waiting list to completely disappear. For example, a mere 5% increase on the number of beds available would lead the percentage of days with waiting list to reduce to half. Even more important, a 15% increase on the number of beads leads the percentage of days with waiting lists to be zero.

The content of part (ii) of Proposition 1 is illustrated in Figure 11.

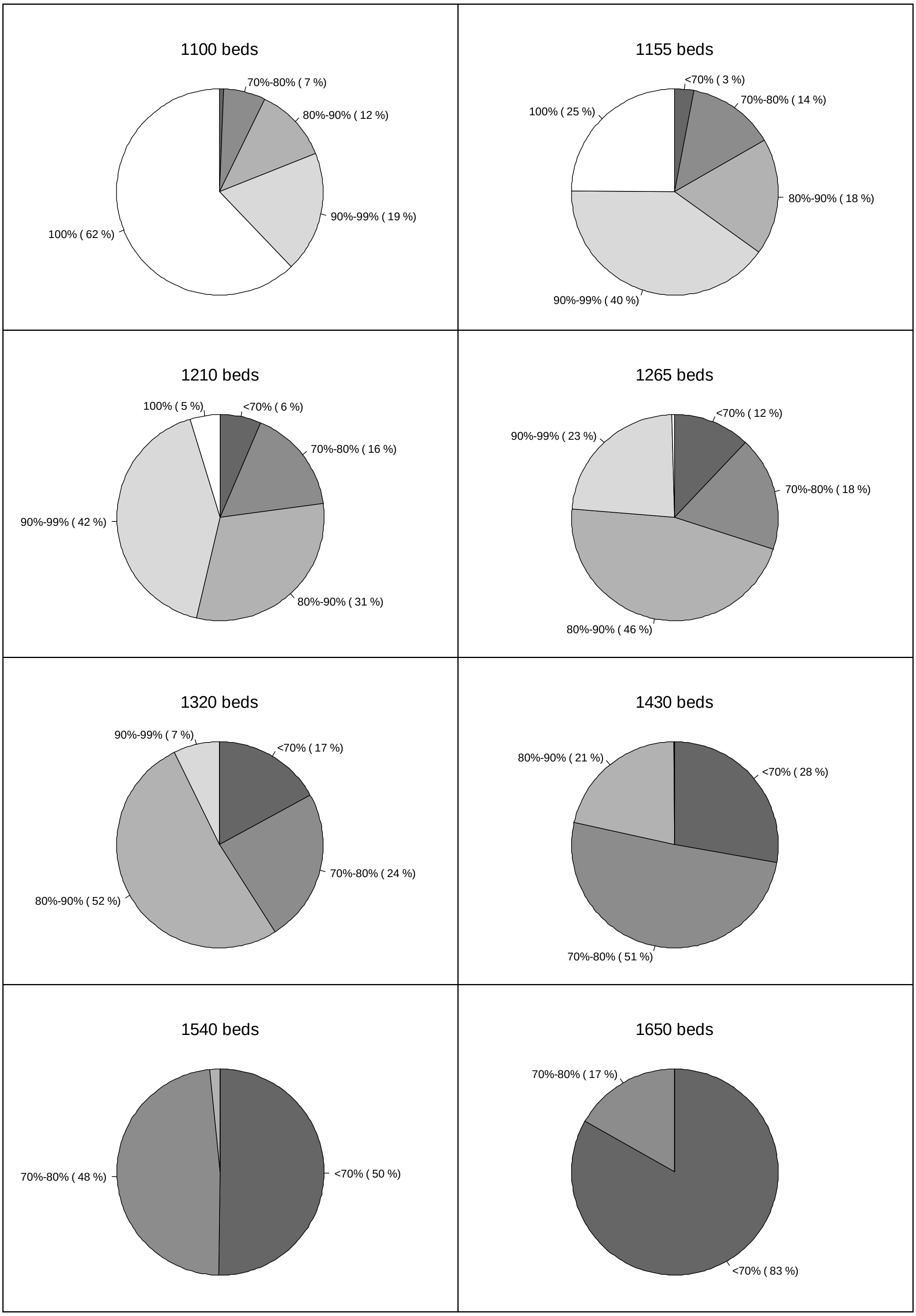


Figure 11. Pie charts for simulated daily occupancy rate.

We can see as a 5% increase in the number of beds reduces the number of days with full occupancy from 62% to 25%. That is, by adding 55 beds to the hospital the reduction of days for which there is full occupancy is very significant. Even more, an increment of 165 beds over the actual number of beds (a 20% increase on hospital beds) would make the hospital not to be fully occupied none day.

3.1.2. Scenario 2

In this case we take the median of the daily inpatient activity in working days (holidays) and the number of beds in working days (holidays) to fit a linear regression. It is well know that if the number of beds increases, the inpatient activity tends to adapt itself to the new productive capacity of the hospital. This effect, known as Roemers' Law (Roemer, 1961), is estimated for a set of 14 Galician hospitals by Reyes et al. (2011). By collecting the number of beds and the inpatient activity of these hospitals, these authors show that the elasticity is 1.44.

Since we are modeling the inpatient activity as a Normal distribution, the pattern of the variable is determined by the mean and the standard deviation. Then we examine if both parameters, the mean and the standard deviation, are linked with the number of beds. To avoid pernicious effects from outliers, we both consider the median and the median absolute deviation (mad) as a robust estimator of dispersion.[4]

The fitted regression model where the covariate is the number of beds in the hospital and the response is the median of the daily inpatient activity is given by:

$$\text{Median (inpatient activity)} = \begin{cases} 3.9619 + .0972 \times \text{Beds, in working days} \\ 4.2362 + .0643 \times \text{Beds, in holidays} \end{cases} \quad (5)$$

and there is a reasonable linear relationship between median of inpatient activity and beds. Indeed, the coefficients of determination for the two fittings are larger than 0.9.

In addition, the fitted regression models where the covariate is the number of beds in the hospital and the response is the mad of the daily inpatient activity is

[4] The mad is the median of the absolute deviations from de data's median. For example, for a dataset as {2,2,3,4,12}, the median is 3, so the absolute deviations from the median are {1,1,0,1,9} (reordered as {0,1,1,1,9}) with a median of 1, in this case unaffected by the value of the outlier 12. Hence, the mad is 1.

$$\text{Mad (inpatient activity)} = \begin{cases} 2.3747 + 0.0165 \times \text{Beds, in working days} \\ 2.2984 + 0.0181 \times \text{Beds, in holidays} \end{cases} \quad (6)$$

where, once more, there is a reasonable linear relationship between mad of inpatient activity and the number of beds. The coefficients of determination for the two fittings are larger than 90%.

Therefore, we can use a modified simulation process where the inpatient activity values for working days are drawn from the Normal distribution $N(\hat{\mu}_W, \hat{\sigma}_W)$, where

$$\hat{\mu}_W = 3.9619 + 0.0972 \times \text{Beds} \text{ and } \hat{\sigma}_W = 2.3747 + 0.0165 \times \text{Beds}, \quad (7)$$

In turn, the inpatient activity values for holidays are drawn from the Normal distribution $N(\hat{\mu}_H, \hat{\sigma}_H)$, where

$$\hat{\mu}_H = 4.2362 + 0.0643 \times \text{Beds} \text{ and } \hat{\sigma}_H = 2.2984 + 0.0181 \times \text{Beds}. \quad (8)$$

Figure 12 and 13 sum up the main results provided by the validated model under the so-called Scenario 2.

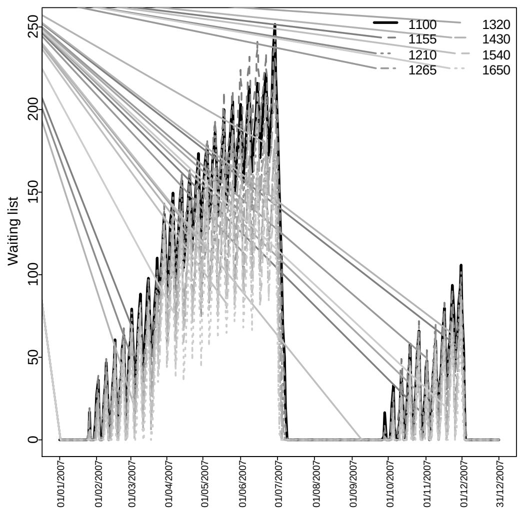


Figure 12. Median of simulated waiting list.

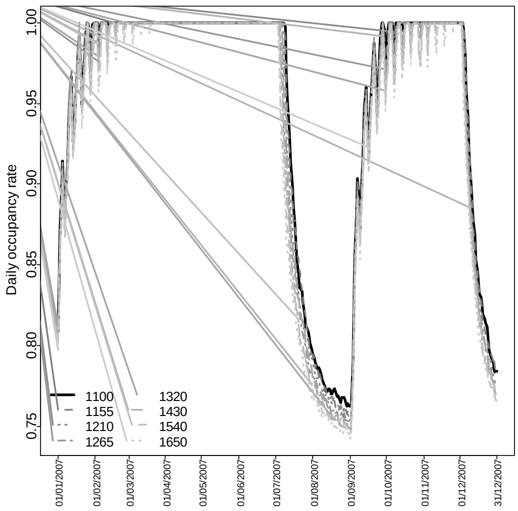
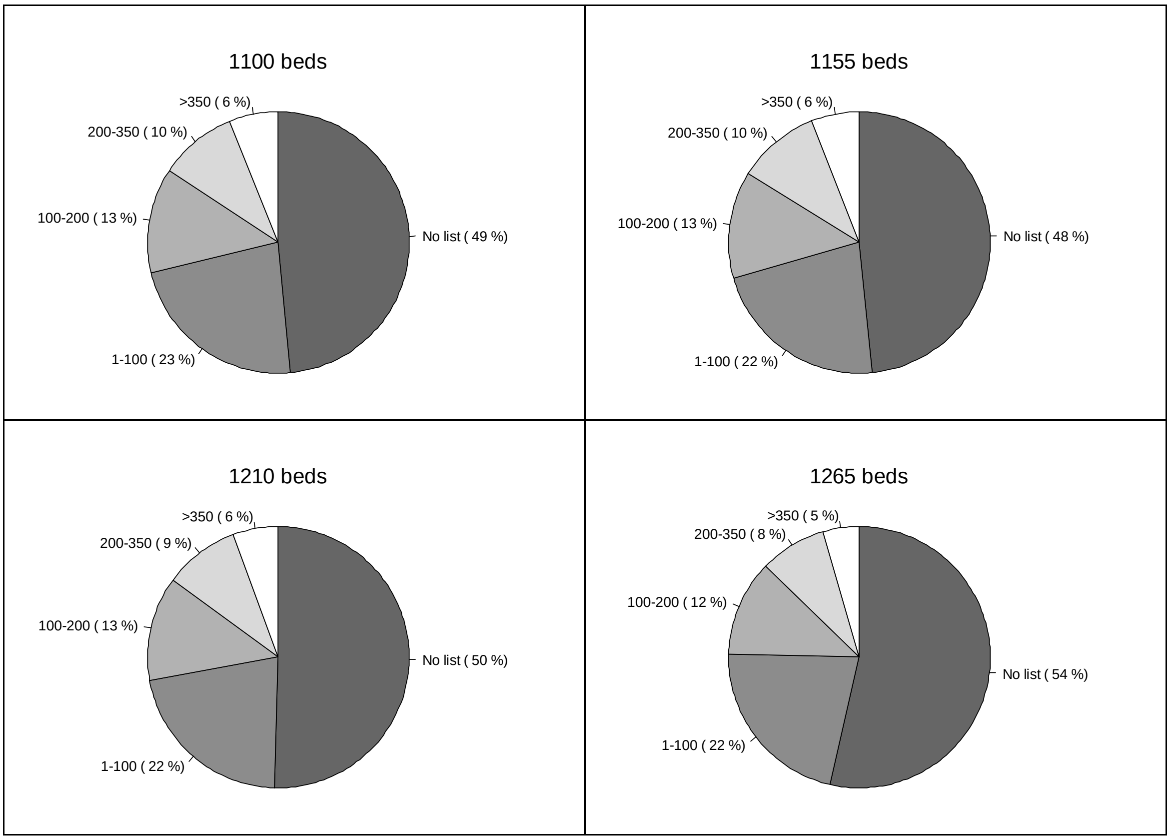


Figure 13. Median of simulated daily occupancy rate.

In Figure 14 se muestra que ahora no es posible eliminar las listas de espera, ni siquiera aumentando en un 50% el número de camas en observación. Por ejemplo, si el aumento en el número de camas es del 5%.



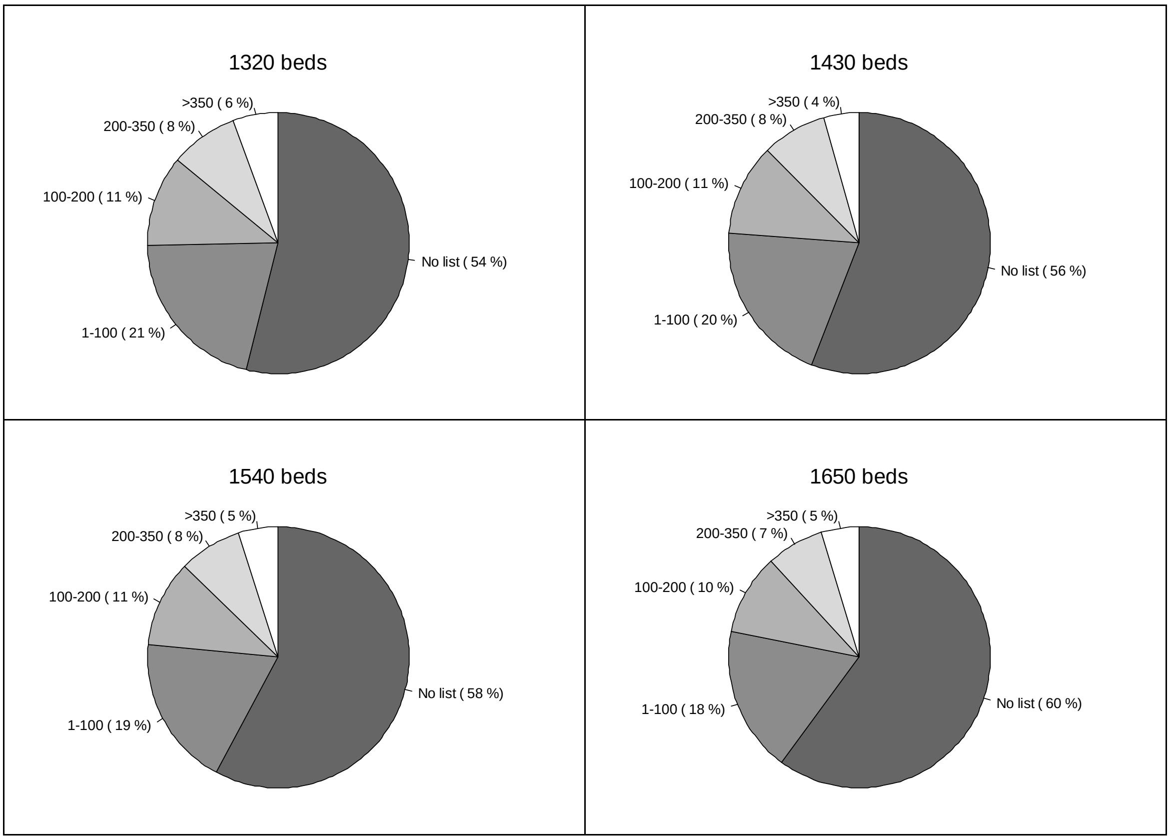
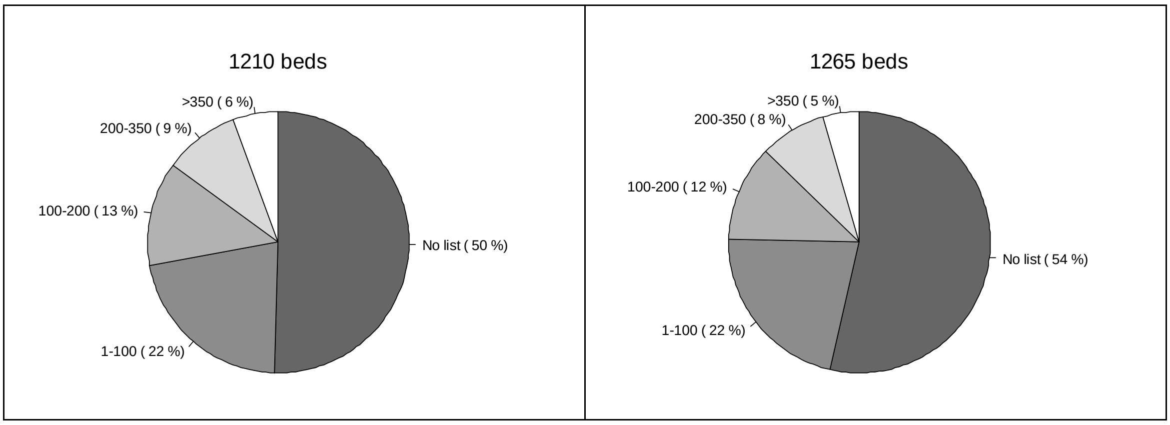


Figure 14. Pie charts for simulated daily waiting list data.



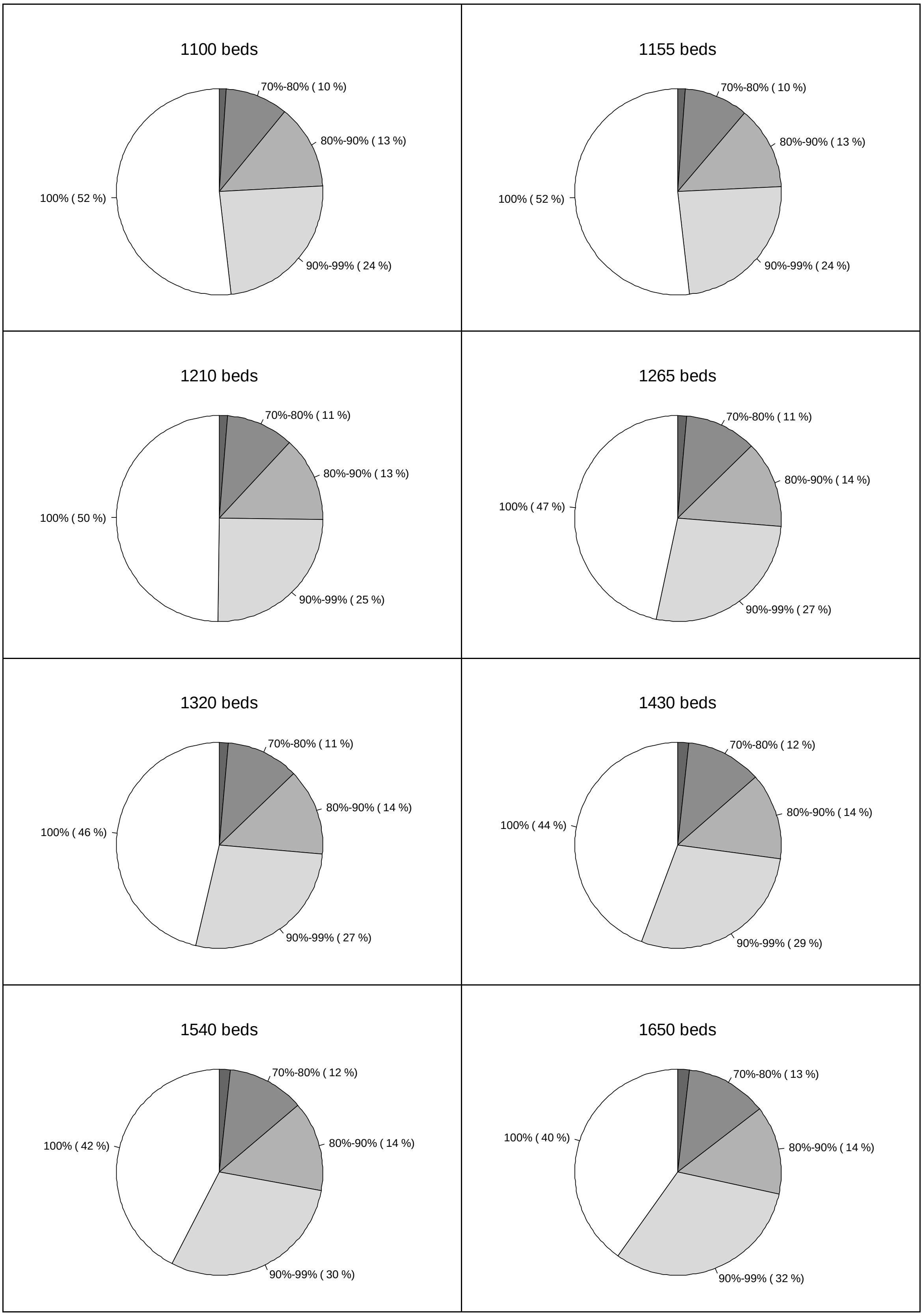


Figure 14. Pie charts for simulated daily occupancy rate.

The simulation results obtained in Scenario 2 can be recorded in the following proposition.

Proposition 2. *If the number of beds has impact on inpatient activity (beds effect), an increase in the number of beds leads to no significant differences in (i) waiting list, even for huge increases, and (ii) occupancy rate.*

4. Discussion

The expansion of physical capacity in a hospital (building new surgical units) is a long-run policy which may require time to be implemented. The increase of the health workforce may be even slower, since physicians and specialists need to be trained for several years before they can become active. Although it is possible to recruit staff from abroad, such staff may encounter assimilation difficulties and such a policy can also take time.

This means that the different ways of increasing supply will generally have different costs and will require different time scales. In the short run it may be possible to purchase extra activity from public facilities at low marginal cost if there is spare capacity. If public facilities are already working close to full capacity, it will be possible to purchase extra activity only at high marginal cost in the short run. In the medium to longer term, it may well be cheaper to expand activity by expanding public capacity. For example, Denmark adjusted its public capacity to respond to the upsurge in demand for coronary revascularisation procedures more rapidly than did England in the 1990s. As a consequence, waiting times for revascularisation fell in Denmark whereas they rose steeply in England.

It is argued that, in principle, waiting times can be reduced through supply-side policies, if the volume of surgery is not considered adequate, or through demand-side policies, if the volume of surgery is considered to be adequate. Supply-side policies include raising public capacity by increasing the number of specialists and beds, or by using the available capacity in the private sector. They also include increasing productivity by funding extra activity, fostering day-surgery, and linking the remuneration system of doctors and hospitals to the activity performed (Hurst and Luigi Siciliani, 2006).

However, it is common to take measures aimed at reducing waiting times by increasing activity, and then find that, after a brief period, demand has increased and waiting times have reverted to levels similar to those before the introduction of the measures.

Such responses may be hard to overcome, since demand responds positively to reductions in waiting times.

The outflow (supply) of elective surgery depends on both public and private surgical capacity and the productivity with which capacity is used. Econometric evidence (of a cross-sectional kind, at national level) suggests that higher capacity, in terms of increased numbers of beds and physicians, is associated with lower waiting times. The supply of elective surgery depends on both public and private surgical capacity and the productivity with which capacity is used. Evidence on the impact of capacity is provided by Martin and Smith (1999) who showed that the waiting time is negatively associated with the number of available beds (elasticity equal to -0.242), using an English database from the Hospital Episode Statistics in fiscal year 1991-92. Similarly, Lindsay and Feigenbaum (1984) found waiting times to be negatively associated with both the number of available doctors and beds.

Even more, Álvarez and Centeno (1999) describe the use of simulation in the Washington Adventist Hospital. At this hospital, simulation was employed to evaluate an expansion in the number of beds in the Emergency Room, which resulted in a reduction of 0.6 hours for average length of stay. Kirtland et al (1995) used simulation to improve performance by reducing the patient`s time in the system and determining the appropriate staffing levels. They studied eleven different alternatives, which resulted in a reduction of thirty eight minutes on the average.

But large increases in capacity may have a different impact on waiting times according to the level of excess demand and of the initial waiting time. Countries with low supply and high initial waiting times are likely to have elastic demand to variations in waiting times. For this reason, the effect of even large increases in capacity on waiting times may be quite modest. (Hurst and Luigi Siciliani, 2006).

In general, supply-side policies may well succeed in their aim of raising the rate of elective surgery but they may be disappointing in their effects on waiting times. That is because an increase in supply may follow rather than lead an increase in demand or may be overtaken by fresh increases in demand. Moreover, any reduction in waiting times may encourage an increase in the rate of entry to queues because of a lowering of clinical thresholds (Hurst and Luigi Siciliani, 2006).

Moreover, many commentators suggested that an increase in the supply of hospital beds tends to generate additional demand either in the form of more patients admitted or patient treated for longer periods of time or some combination of two (Zeraati et al, 2005).

Formerly, Shain and Roemer (1959), found very close correlations between the availability of short term general hospital beds per 1000 population and rates of utilization as measured by hospital days per 1000 population. Roemer and Milton (1961) also reported on a natural experiment where a sudden increase in hospital beds in one country, with no changes in other factors, led to a sharp increase in utilization rates. Roemer`s Law.

It is worth noting that, while the use of simulation models in health care is not new, one survey of 200 health-care simulation models demonstrates that their results were implemented in only 16 cases, showing how their acceptance has been limited (Tunnicliffe-Wilson, 1981)

According to Álvarez and Centeno (1999), the primary reason for the reluctance of the health care industry to accept simulation was the management`s reluctance to reduce complex process in the health care field to a model representation.

5. Concluding remarks

The expected positive sign for bed supply has been indeed found. Admission rates appear to be sensitive to bed supply.

References

Akkerman, R. and R. Knipp (2004), Reallocating of beds to reduce waiting time for cardiac surgery, *Health Care Management Science* 7, 119-126.

R Development Core Team, R (2010), *A Language and Environment for Statistical Computing*, R Foundation for Statistical Computing, Vienna, Austria. (Available at <http://www.R-poject.org>.)

Davies, R. and T.T.O. Davies (1994), Modelling patient flows and resources provision in health systems, *Omega International Journal of Management Science* 22, 123-131.

Law, A.M. and W.D. Kelton (1991), *Simulation Modelling and Analysis*, McGraw-Hill, New York, 2nd ed.

Wand, M.P. and M.C. Jones (1995), *Kernel Smoothing*, Chapman & Hall, London.

Reyes-Santías, F., C. Cadarso-Suárez, and A. Martínez-Calvo (2011), Applying a simulation model to manage waiting lists for hospital inpatient activity in a EU región, *Mathematical and Computer Modelling* (forthcoming).

Denton, B., J. Viapiano, and A. Vogl (2007), Optimization of surgery sequencing and scheduling decisions under uncertainty, *Health Care Management Science* 10, 13-24.

Everett, J.E. (2002), A decision support simulation model for the management of an elective surgery waiting system, *Health Care Management Science* 5, 89-95.

Zeraati, H., F. Zayeri, G. Babae, N. Khanafshar, and F. Ramezanzadeh (2005), Required hospital beds estimation: A simulation study, *Journal of Applied Sciences* 5, 1189-1191.

Kroneman, M. and J.J. Siegers (2004), The effect of hospital bed reduction on the use of beds: A comparative study of 10 European countries, *Social Science & Medicine* 59, 1731-1740.

Roemer, M.I. (1961), Bed supply and hospital utilization: A national experiment, *Hospitals: JAHA* 35, 988-993.

Siciliani, L. and J. Hurst (2003), Explaining waiting times variations for elective surgery across OECD countries, OECD Health Working Papers 7.

Lapierre, D. and A. Ruiz (2007), Scheduling logistic activities to improve hospital supply systems, *Computers and Operations Research* 34, 624-641.

Alvarez, A. and M. Centeno (1999), Enhancing simulation models for emergency rooms using VBA, Winter Simulation Conference, 1685-1693.

Richards…

Yamaguchi et al. (1994).

Silber et al…

Sampietro and Espallargues, 2001

Churruca (2000)

NHS Scotland Workforce Statistics, 2006

VanBerkel, P.T. and J.T. Blake (2007), A comprehensive simulation for wait time reduction and capacity planning applied to general surgery, *Health Care Management Science* 10, 373-385.